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Predicting Factors Behind Students' Perceived Usefulness and Behavioral Intention to Adopt E-Learning: A Case Study of a Private University in Zhanjiang, China

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Abstract

Purpose: This study established a novel conceptual model to conduct an in-depth analysis and clarify the composition of the key factors influencing the e-learning behavioral intention of students in private undergraduate colleges in Zhanjiang, China. Concurrently, this research underscores how students' perceived ease of use influences their perceived usefulness, subsequently divulging the inherent correlation between these two factors. **Research design, data, and methodology:** This research endeavors to undertake quantitative data collection and analysis. In the sampling process, non-probability sampling approaches were employed, encompassing judgment sampling for selecting four representative secondary colleges, quota sampling for determining the sample size, and convenience sampling for the actual data collection. The researcher devised and executed an online survey and successfully gathered 500 valid questionnaires. In the data analysis stage, the researchers utilized two statistical methods: Structural Equation Modeling (SEM) and Confirmatory Factor Analysis (CFA). **Results:** Research data reveals that multiple factors, including perceived ease of use, perceived usefulness, performance expectancy, effort expectancy, social influence, and attitude, positively enhance students' behavioral intention toward e-learning. Among them, perceived ease of use and social influence have notable promoting effects on behavioral intention. **Conclusions:** This study offers a novel perspective for comprehending learners' perceived usefulness of e-learning technology and its relationship with behavioral intention and establishes a strong groundwork for subsequent related research.

Keywords: Perceived Ease of Use, Perceived Usefulness, Performance Expectancy, Effort Expectancy, Social Influence

JEL Classification Code: E44, F31, F37, G15

1. Introduction

In the twentieth century, the trend of profound integration between Information and Communication Technologies (ICT) and the domain of education was remarkable, and this trend impelled higher education institutions in numerous countries across the globe to embrace the e-learning model (Ouadoud et al., 2021). Scholars from diverse nations have proffered disparate viewpoints on the definition of e-learning. Liu (2010) contends that e-learning is a modality that employs information technology to facilitate users in accomplishing learning or teaching activities. Kongchan's (2012) viewpoint is based on this perspective, and he defines e-learning as the application of information to the learning and teaching process within the confines of communication technology networks. Ratheeswari (2018) indicated that e-learning is a learning approach based on the Internet or extranet, which facilitates online interaction between teachers and students and enables the online completion of coursework plans. E-learning encompasses many methods, with web-based learning playing a significant role (Tinio, 2002). To recapitulate, e-learning, also known as distance learning, has its operational mechanism deeply entrenched in computer technology, the Internet, and an extensive range of computer network systems (Awada, 2016). This model not only relies on the vigorous support of computer technology

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but also hinges on the prevalence of the Internet and the seamless connection of computer networks. It allows learners to access learning resources at any moment and in any location and facilitates global engagement and exchange between educators and learners through digital platforms. It has significantly broadened the boundaries and horizons of learning.

For developing countries, despite the relatively sluggish progress of e-learning in the educational domain, it has garnered profound attention from numerous national educational institutions. It has been vigorously incorporated into the modern teaching reform process. Specifically, Tabuk University in Saudi Arabia has taken the initiative by introducing the e-learning system in teaching to stimulate students' academic interest and enhance their academic performance (Bellaaj et al., 2015). Meanwhile, the University of Malaysia effectively utilizes e-learning benefits to enhance the teaching environment and strengthen teacher-student interaction using various instructional methods (Zawaideh, 2017). In India, Nishi-Magasti University is not trailing either and has extensively applied e-learning in the daily lectures for postgraduate students (Mahande & Malago, 2019). In China, since 2019, in the "Guiding Opinions on Promoting the Healthy Development of Online Education" jointly issued by a total of 11 departments, including the National Development and Reform Commission, the core significance of vigorously developing comprehensive online education and its current urgency has been explicitly and forcefully emphasized. Against this backdrop, the academic circle in China has been paying escalating attention to the e-learning system. Many scholars generally contend that e-learning can effectively replicate teachers' teaching activities and furnish students with personalized learning experiences, thereby significantly enhancing teaching efficacy (Chen, 2017; He et al., 2016; Song, 2022).

As an emergent educational paradigm, E-learning still has scope for enhancement in integrating offline teaching and online resources and transforming the teaching model of higher education. In the e-learning milieu, one significant challenge educators encounter is the difficulty of obtaining prompt feedback from students concerning their teaching approaches. Because teachers and students are in disparate time and space, and the opportunities for face-to-face communication diminish, it is arduous to guarantee the teaching effect of e-learning (Wang, 2024). Moreover, when there is inadequate teacher oversight, students' self-control has been identified as a contributing factor affecting the successful execution of e-learning (Huang, 2021). There remain areas for improvement in the quality guarantee of e-learning platforms and software, and whether students perceive the system's usefulness constitutes a challenge to the behavioral intention of students to utilize e-learning in higher education (Yang et al., 2022). Many scholars commonly hold that the anticipated outcomes of E-learning have yet to be fully attained. In China, the majority of studies center on exploring the relationship between perceived ease of use, perceived usefulness, and satisfaction or the intention to continue learning by employing the TAM model (Qin et al., 2020; Song, 2023; Yang, 2016, 2020), or analyzing the factors affecting students' learning behavioral intention based on the UTAUT model (Hu & Zhang, 2024; Xiong, 2023; Zhang et al., 2022). However, limited studies have developed innovative conceptual frameworks to thoroughly investigate the elements impacting college students' perceived usefulness and intention to engage in e-learning. Despite E-learning's numerous benefits, it is accompanied by numerous challenges and difficulties. This study takes students from private undergraduate colleges in Zhanjiang City, China, as the subject, seeking to explore the determinants of undergraduate students' perceived usefulness and behavioral intention to use e-learning and propose targeted reform suggestions to enhance the effect of e-learning.

2. Literature Review

2.1 Perceived Ease of Use

In the e-learning environment, prior research has demonstrated a strong correlation between perceived ease of use and perceived usefulness (Pituch & Lee, 2006). Lin (2011) further indicated that the correlation between perceived usefulness and ease of use is stronger when users are unfamiliar with the online learning approach. Specifically, when users deem a certain technology easy to operate and believe it can enhance their work or study efficiency, the importance of perceived ease of use in predicting perceived usefulness cannot be overstated. (Abdullah et al., 2016).

Mailizar et al. (2021) manifested that the ease of use of the e-learning system and the extent of energy savings perceived by undergraduates when using the system contribute to their perceived usefulness in fulfilling their academic life. Educational institutions in numerous countries have conducted in-depth investigations into the correlation between perceived ease of use and perceived usefulness. An empirical study on the mobile learning services adopted by online universities in Korea revealed that when the user interface and personal innovation elements were incorporated into mobile learning, the perceived ease of use of mobile learning by college students significantly predicted their perceived usefulness (Joo et al., 2014). Students in Saudi undergraduate educational institutions noted that when they perceived the ease of use of a new project and did not require mental exertion, their perceived usefulness increased significantly (Binyamin et al., 2019).

The research conducted by Shah and Attiq (2016) reveals that users' perceived ease of use of a platform can significantly predict the degree of their behavioural intentions, and perceived usefulness serves as a mediating variable in this process (Sánchez-Franco et al., 2009). Yang and Yoo (2004) and Cigdem and Topcu (2015) argue that perceived ease of use plays a less significant role than perceived usefulness in predicting behavioural intention, academic perspectives also hold different viewpoints. Perceived ease of use is regarded as playing a crucial role. Venkatesh's (2000) research emphasizes this aspect. He indicates that when confronted with emerging technologies, perceived ease of use is a key determinant for users' acceptance willingness and subsequent usage behaviors.

H1: Perceived ease of use has a significant impact on perceived usefulness.

H2: Perceived ease of use has a significant impact on behavioural intention.

2.2 Perceived Usefulness

Davis (1989) asserted that perceived usefulness is the most significant predictor of behavioral intention. Al-Aulamie et al. (2012) explicitly stated that perceived usefulness positively and objectively influences user behavioral intention. As a crucial factor, it can profoundly affect users' willingness to adopt and utilize technology. Specifically, when information technology is perceived as practical by users, they will generate a more affirmative willingness to employ it. This perspective has received further support from Budu et al. (2018), who indicated that perceived usefulness can profoundly impact and permeate an individual's behavioral intention.

Scholars argue that the perceived value of e-learning platforms is beneficial in encouraging students to adopt them, and the continuous accumulation of knowledge further fortifies this perceived usefulness (Chang et al., 2017). Specifically, when students fully acknowledge the practical utility of the e-learning platform, this recognition will prompt them to enhance their positive behavioral motivation for using these platforms (Binyamin et al., 2019).

The greater the perceived usefulness of the e-learning platform for an individual, the more likely they are to express their intention to use it, and it directly affects the adoption of the system (Cheng, 2014; Yang & Yoo, 2004). Before the acceptance of perceived ease of use, the direct prediction of users' behavioral intention towards e-learning is based on perceived usefulness (Mohammadi, 2015). Therefore, the study proposes the following hypotheses:

H3: Perceived usefulness has a significant impact on behavioral intention.

2.3 Performance Expectancy

Performance expectancy characteristics manifest in individuals' firm conviction that information technology can elevate their performance level and augment their intention to utilize it (Muangmee et al., 2021). Potential users anticipate that adopting new technologies will yield a substantial increase in productivity, thereby indicating that performance expectancy exhibits the most prominent and reliable predictive potency when forecasting their behavioral intention to employ new technologies (Masadeh et al., 2016).

The research by Abu-Al-Aish and Love (2013) explicitly stated that in contrast to the student group with lower expected grades, students with higher expected grades demonstrate a stronger inclination and are prone to using the mobile learning system. When contemplating the profound impact of performance expectancy on the mobile learning environment, this finding predicts that students will view mobile learning as a convenient means to enhance academic success effectively. Similarly, in the empirical investigation carried out by Mahande and Malago (2019) regarding the acceptance of e-learning, performance expectancy was identified as a crucial element that substantially impacts undergraduates' behavioural intention to embrace the e-learning initiative.

It has been discovered that an effectively performing e-learning system can successfully enhance students' classroom performance and academic achievements, and performance expectancy plays a crucial role in intensifying the inclination of students to employ the e-learning system (Jameel et al., 2020). In the e-learning context, when educators believe that e-learning can generate high-quality work outcomes, performance expectancy is promptly formed. Subsequently, it promotes a more affirmative behavioural intention to use the system (Thongsri et al., 2019). Therefore, the study proposes the following hypotheses:

H4: Performance expectancy has a significant impact on behavioural intention.

2.4 Effort Expectancy

When users contemplate that the technology they employ does not demand additional exertion, they will shape effort expectancy, which constitutes one factor that stimulates users' behavioural intentions (Odegbesan et al., 2019). Effort expectancy is considered one of the indispensable determinants for forecasting individual usage behavior. When individuals perceive the technology is facile, their behavioural intention to utilize it will exhibit a more affirmative tendency (Shaqrah, 2015).

When users believe that information technology can bring convenience to their work, their willingness to adopt it will increase correspondingly, promoting the synergy effect of effort expectancy on their behavioural intentions (Nahla Aljojo, 2020). In the relevant research on the determinants of e-learning, Liao et al. (2011) explicitly pointed out that the alteration in the expected effort required will directly result in a change in an individual's willingness to employ the technology.

According to the study by Altameemi and Al-Slehat (2021), when e-learning programs are perceived as user-friendly by users, users tend to use these programs more actively. The study also highlights that enhancing effort expectancy is a key element in strengthening an individual's behavioral willingness to participate in such learning programs. Chao (2019) indicated that students' conviction that the system can enhance their academic performance will positively influence their willingness to utilize the system, and effort expectancy can predict students' behavioral intentions in mobile learning programs. Muangmee et al. (2021) emphasized that effort expectancy plays a crucial role in determining an individual's behavioural willingness to adopt e-learning technology in learning behaviours. Therefore, the study proposes the following hypotheses:

H5: Effort expectancy has a significant impact on behavioural intention.

2.5 Social Influence

Zhang et al. (2022) contended that users are prone to communicate with others regarding their acceptance of technology and attach considerable significance to the opinions of others, which exerts a direct positive influence on their behavioural intentions. Based on common knowledge, when people embrace new technologies, social influence substantially Molds their behavioural intentions (Odegbesan et al., 2019). Users deem that colleagues, peers, and relatives largely impact their interest in the new system, and this social influence constitutes a key factor in stimulating personal behavioural intentions (Vululleh, 2018).

In an educational setting, students attach greater importance to the viewpoints of their peers and teachers on their utilization of technology. As a positive force, social influence significantly boosts students' adoption and behavioral intentions toward the learning system (Tarhini et al., 2017). Given the inherently social nature of human beings, the interaction patterns between students tea, teachers, and peers profoundly affect their cognitive construction of behavioural intentions toward emerging technologies. Among them, social influence is pivotal in determining the depth and breadth of this influence (Muangmee et al., 2021). Olasina (2019) emphasized that the influence of significant others is particularly prominent in shaping individuals' concepts and preferences. This observation reveals that social influence positively impacts encouraging individuals' intentions to adopt information technology behaviours.

The study by Altameemi and Al-Slehat (2021) revealed that the acceptance of e-learning in higher education was significantly influenced by social influences such as lecturers and classmates. The study explicitly pointed out that social influence played a positive and crucial role in shaping students' behavioural intentions toward the online learning model. At the same time, the survey outcomes of Faqih (2020) also supported this point, indicating that individuals' acceptance attitudes and behavioural practices toward new technologies are largely shaped and guided by social influence. In addition, as users' social influence escalates, their intentions to accept and adopt new technologies also demonstrate a corresponding ascending trend. Therefore, the study proposes the following hypotheses:

H6: Social influence has a significant impact on behavioural intention.

2.6 Attitude

Attitude pertains to an individual's cognition and psychological response to technology. Its positivity can potently stimulate an individual's behavioural intention to adopt technology (Liu et al., 2009). Boateng et al. (2016) contend that attitude essentially mirrors an individual's emotional propensity towards a specific behavioural objective, whether positive or negative. This emotional propensity, as an internal driving force, urges individuals to engender a more vigorous behavioural intention to utilize technology effectively.

According to the research of Cheung and Vogel (2013), fostering a favourable attitude toward the use of information technology is of paramount significance for shaping the behavioural intention of potential users. Attitude significantly influences users' expected level of acceptance of e-learning and their willingness to participate, ultimately determining individual behavioral intention formation (Jere, 2020). Attitude, as the emotional propensity of students to adopt e-learning, its pleasantness, and positivity are regarded as core indicators for gauging high behavioral intention (Rabaai, 2016).

Research on e-learning suggests that when users maintain a proactive and positive attitude towards e-learning, their behavioral willingness to accept e-learning will be higher (Ndubisi, 2004). Chu and Chen (2016) indicate that their attitude profoundly influences the degree of interest of learners, and this attitude is directly correlated with and affects their behavioral intention to participate in e-learning. When students hold a positive attitude towards e-learning, their perception of the effect of e-learning tends to be optimistic, thereby significantly enhancing their behavioral willingness to participate in e-learning (Buabeng-Andoh,

2021). Therefore, the study proposes the following hypotheses:
H7: Attitude has a significant impact on behavioral intention.

2.7 Behavioral Intentions

Behavioral intention is the extent of an individual's awareness of their inclination to engage in a particular behavior (Davis, 1989). According to Ajzen (1991), behavioral intention refers to an individual's inclination to perform a particular action and is considered a pivotal determinant in forecasting subsequent actual behavior. In the technological realm, behavioral intention is specified as the propensity to continue employing a certain technology in the future, and this propensity directly determines the degree of acceptance of the technology (Alharbi & Drew, 2014). Behavioral intention pertains to the likelihood of students utilizing the e-learning platform, provided accessible technologies are available (Budu et al., 2018).

3. Research Methods and Materials

3.1 Research Framework

Under the contemporary educational backdrop, e-learning, serving as an auxiliary modality of offline education, has witnessed an increasingly prominent significance. The conceptual framework of this research project is grounded in three well-recognized classical theories. The first model is the Technology Acceptance Model (TAM) (Davis et al., 1989). The second one is predicated on the theory of Venkatesh et al. (2003), namely the Unified Theory of Acceptance and Use of Technology (UTAUT). The third is the Theory of Planned Behavior (TPB), derived through meticulous research by Ajzen (1991). The researchers put forward a new conceptual framework on this foundation, as depicted in Figure 1.

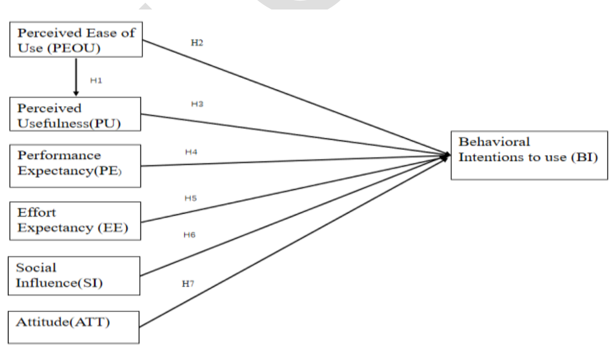

Figure 1: Conceptual Framework

H1: Perceived ease of use has a significant impact on perceived usefulness.
H2: Perceived ease of use has a significant impact on behavioral intention.
H3: Perceived usefulness has a significant impact on behavioral intention.
H4: Performance expectancy has a significant impact on behavioral intention.
H5: Effort expectancy has a significant impact on behavioral intention.
H6: Social influence has a significant impact on behavioral intention.
H7: Attitude has a significant impact on behavioral intention.

3.2 Research Methodology

This study selected students from four representative secondary colleges within Zhanjiang University of Science and Technology as the survey subjects. Given their considerable student population, these colleges can fully represent the characteristics of the Zhanjiang University of Science and Technology student group. The four colleges share an identical basic public curriculum system, guaranteeing that students possess a solid foundation of academic literacy. During the survey process, students participated in the questionnaire on the principle of voluntariness. The questionnaire structure of this study is meticulously designed and comprises three major sections. The first part focuses on establishing screening questions to position the surveyed group precisely. The second part thoroughly presents the five-point Likert scale, which comprehensively encompasses this study's seven hypotheses. The subjects assigned ratings to individual items within the range from "1" to "5", ranging from "strongly disagree" to "strongly agree," to guarantee the comprehensiveness and accuracy of the data. The third part centers on the collection of demographic information, specifically covering the gender, age, grade level, and academic year of the respondents.

The collection of questionnaires adhered to a rigorous procedure. A pilot test was conducted, and 50 eligible samples were successfully collected from the four colleges. The questionnaire underwent a strict review by three experts, confirming its consistency with the project and objectives. The Cronbach Alpha method was employed to assess reliability, a highly significant indicator for evaluating reliability (Tavakol & Dennick, 2011). The pilot test results verified the internal consistency of the questionnaire's conceptual framework and further substantiated its reliability.

3.3 Population and Sample Size

After the success of the pilot test, the research team fully distributed the questionnaires to students of the four colleges and ultimately successfully collected 500 valid questionnaires. To conduct an in-depth analysis of these data, the study adopted two potent and flexible statistical methods: Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM). Confirmatory factor analysis (CFA) was utilized to test the measurement model's convergent validity and discriminant validity (Anderson & Gerbing, 1988). Structural equation modeling is driven by specific theories and is applied to various techniques to detect causal links between variables (Hair et al., 2006). The study conducted a thorough factor analysis and regression analysis of the data by combining these two methods, thereby verifying the theoretical hypotheses and the relationships among various variables and behavioral intentions.

3.4 Sampling Technique

This research meticulously chose the college student groups from four secondary colleges within the jurisdiction of Zhanjiang University of Science and Technology as the subjects of this investigation through the combination of judgmental or purposive Sampling, stratification random sampling, and convenient Sampling. To guarantee the comprehensiveness and accuracy of data collection, a professional online questionnaire survey platform was utilized, and electronic questionnaires were distributed to the target groups. Table 1 details the sampling results and distribution of this study.

Table 1: Sample Units and Sample Size

Primary and Secondary Schools	Population Size	Proportional Sample Size
Economics and Finance college	2500	115
Intelligent Manufacturing college	3923	180
Architectural and Engineering college	1850	85
Accounting college	2600	120
Total	**10873**	**500**

Source: Constructed by author

4. Results and Discussion

4.1 Demographic Information

During the questionnaire design process, the respondents' demographic characteristics are considered to be one of the essential key elements (Polonsky & Waller, 2018). Scholars like Purdie et al. (2002) indicated that when formulating questionnaire questions, demographic factors, including age, marital status, gender, family structure, income level, and place of residence, should be fully considered to guarantee the comprehensiveness and accuracy of the survey.

Based on the abovementioned principles, this study surveyed 500 undergraduates from four secondary colleges of Zhanjiang University of Science and Technology. Among the collected samples, there were 263 female respondents, constituting 52.6%, while there were 237 male respondents, accounting for 47.4%. Regarding the grade distribution, there were 178 sophomores, representing 35.6% of the overall sample; 197 juniors, accounting for 39.4%; and 125 seniors, making up 25%. Additionally, regarding the age distribution of the respondents, there were a total of 152 students aged 19-20, representing 30.4% of the overall sample; there were 277 students aged 20-21, accounting for as much as 55.4%, while there were 71 students aged 23 and above, accounting for 14.2%. Table 2 provides a detailed overview of the demographic data from this research.

Table 2: Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Gender	female	263	52.6%
	male	237	47.4%
Age	19-20 years old	152	30.4%
	21-22 years old	277	55.4%
	23 years old and above	71	14.2%
Year of Study	Sophomore	178	35.6%
	Junior	197	39.4%
	Senior	125	25%

4.2 Confirmatory Factor Analysis (CFA)

The data analysis process of this study strictly adhered to the two-stage strategy (Anderson & Gerbing, 1988). In the initial phase, confirmatory factor analysis (CFA) was performed to ascertain and verify the rationality and validity of the measurement model. During the second phase, the structural equation model (SEM) was utilized for a systematic examination and analysis to explore the potential causal relationships between the various constructs thoroughly. The entire analysis process was supported by the professional software program Analysis of Moment Structures (AMOS), guaranteeing the rigor and scientificity of the analysis results.

The measurement model precisely delineated the latent variables, and the validity of these variables was affirmed by confirmatory factor analysis (Suhr, 2006). When assessing the convergent validity, the criteria proposed by Fornell and Larcker (1981) were adhered to, namely, the construct reliability (CR) is required to exceed 0.6, and the average variance extracted (AVE) should be greater than 0.4. This study's CR and AVE outcomes were higher than the established thresholds. Additionally, the Cronbach Alpha values of all structures surpassed the minimum threshold of 0.7, guaranteeing the internal coherence of the structures

(Hair et al., 2010). Factor loading is also a metric for evaluating convergent validity, and a factor loading above 0.5 is an acceptable criterion (Hair et al., 2010). The reliability and convergence of all structures satisfied the threshold requirements, and the results are presented in Table 3.

Table 3: Confirmatory Factor Analysis Result, Composite Reliability (CR) and Average Variance Extracted (AVE)

Variables	Source of Questionnaire (Measurement Indicator)	No. of Item	Cronbach's Alpha	Factors Loading	CR	AVE
Perceived Ease of Use (PEOU)	Lee (2006)	3	0.795	0.736-0.763	0.795	0.564
Perceived Usefulness (PU)	Cheng (2014)	3	0.803	0.726-0.814	0.804	0.578
Performance Expectancy (PE)	Perera and Abeysekera (2022)	4	0.862	0.747-0.812	0.862	0.610
Effort Expectancy (EE)	Twum et al. (2022)	3	0.818	0.761-0.796	0.819	0.601
Social Influence (SI)	Twum et al. (2022)	3	0.815	0.746-0.800	0.817	0.598
Attitude (ATT)	Tsai et al. (2018)	4	0.840	0.723-0.776	0.840	0.569
Behavioral Intention (BI)	Abbas (2016)	3	0.803	0.747-0.765	0.802	0.575

In the CFA test of this study, GFI, AGFI, NFI, CFI, TLI, and RMSEA were employed as crucial indicators for assessing the model fit. Table 4 presents the fit indices of this study and the acceptable thresholds.

Table 4: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/df	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	1.165
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.960
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.948
NFI	≥ 0.80 (Wu & Wang, 2006)	0.952
CFI	≥ 0.80 (Bentler, 1990)	0.993
TLI	≥ 0.80 (Sharma et al., 2005)	0.991
RMSEA	< 0.08 (Pedroso et al., 2016)	0.018
Model Summary		**Acceptable Model Fit**

Remark: CMIN/DF = the ratio of the chi-square value to degree of freedom, GFI = goodness-of-fit index, AGFI = adjusted goodness-of-fit index, NFI = normalized fit index, CFI = comparative fit index, TLI = Tucker Lewis index, and RMSEA = root mean square error of approximation

Table 5 presents the fit indices of this study and the acceptable thresholds.

Table 5: Discriminant Validity

	PEOU	PU	PE	EE	SI	ATT	BI
PEOU	**0.751**						
PU	0.397	**0.760**					
PE	0.289	0.172	**0.780**				
EE	0.326	0.246	0.236	**0.775**			
SI	0.472	0.32	0.306	0.326	**0.773**		
ATT	0.339	0.285	0.301	0.302	0.386	**0.754**	
BI	0.464	0.395	0.323	0.361	0.475	0.389	**0.758**

Note: The diagonally listed value is the AVE square roots of the variables
Source: Created by the author.

4.3 Structural Equation Model (SEM)

The structural model mirrors the associations or pathways among latent variables, namely, the direct or indirect impacts among variables (Byrne, 2010). Grounded on the previous research findings, the overall fit indices of the structural model: the ratio of chi-square to degrees of freedom (CMIN/DF) is less than 5.00; GFI is greater than 0.85; AGFI, NFI, CFI, and TLI are all greater than 0.80, and RMSEA is less than 0.08 (Al-Mamary & Shamsuddin, 2015; Awang, 2012; Bentler, 1990; Pedroso et al., 2016; Sharma et al., 2005; Sica & Ghisi, 2007; Wu & Wang, 2006). The researchers employed AMOS software for computation. The outcomes indicated that the model was well-suited to the data, with CMIN/df = 3.002, GFI = 0.875, AGFI = 0.845, NFI = 0.869, CFI = 0.908, TLI = 0.895, and RMSEA = 0.063. The values of each index are presented in Table 6.

Table 6: Goodness of Fit for Structural Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/df	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	3.002
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.875
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.845
NFI	≥ 0.80 (Wu & Wang, 2006)	0.869
CFI	≥ 0.80 (Bentler, 1990)	0.908
TLI	≥ 0.80 (Sharma et al., 2005)	0.895
RMSEA	< 0.08 (Pedroso et al., 2016)	0.063
Model Summary		**Acceptable Model Fit**

Remark: CMIN/DF = the ratio of the chi-square value to degree of freedom, GFI = goodness-of-fit index, AGFI = adjusted goodness-of-fit index, NFI = normalized fit index, CFI = comparative fit index, TLI = Tucker Lewis index, and RMSEA = root mean square error of approximation

4.4 Research Hypothesis Testing Result

The causal path's nature was evaluated using standardized path coefficients (b) and t-values, as illustrated in Table 7. Drawing upon the Technology Acceptance Model (TAM) and its subsequent extensions, the interrelationships among perceived usefulness (PU), perceived ease of use (PEOU), and behavioral intention (BI) were established. PEOU was found to have a substantial impact on PU ($\beta = 0.494$, $p < 0.001$), thereby supporting H1. Perceived ease of use (PEOU) served as an effective predictor of perceived usefulness (PU). PEOU significantly affected BI ($\beta = 0.246$, $p < 0.001$), confirming H2. Perceived ease of use (PEOU) effectively forecasted behavioral intention (BI). PU significantly impacted BI ($\beta = 0.229$, $p < 0.001$), supporting H3. Perceived usefulness (PU) effectively predicted behavioral intention (BI).

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-value	Result
H1: PEOU→PU	0.494	8.253*	Supported
H2: PEOU→BI	0.246	3.814*	Supported
H3: PU→BI	0.229	3.596*	Supported
H4: PE→BI	0.149	2.989*	Supported
H5: EE→BI	0.185	3.593*	Supported
H6: SI→BI	0.306	5.669*	Supported
H7: ATT→BI	0.179	3.517*	Supported

Note: * p<0.05
Source: Created by the author

The outcomes of this study demonstrate that PE has a positive and significant influence on BI ($\beta = 0.149$, $p < 0.05$). This discovery substantiates Hypothesis H4, namely, performance expectancy (PE) is one of the key factors driving the formation of behavioral intention (BI). The predictive impact of EE on BI is significant ($\beta = 0.185$, $p < 0.001$). This result validates Hypothesis H5, suggesting that effort expectancy (EE) is also an important element affecting behavioral intention (BI). The predictive effect of SI on BI is highly significant ($\beta = 0.306$, $p < 0.001$). This finding confirms Hypothesis H6: social influence (SI) plays a vital role in driving behavioral intention (BI).

Utilizing the Theory of Planned Behavior (TPB) as its framework, this study explores the correlation between attitudes (ATT) and behavioral intentions (BI). The attitude (ATT) demonstrates a substantial ability to forecast behavioral intention (BI) ($\beta = 0.179$, $p < 0.001$). This discovery provides robust evidence for H7, indicating that attitude (ATT) positively influences behavioral intention (BI) prediction.

5. Conclusion and Recommendation

5.1 Conclusion

This research presented a conceptual model and empirically examined the various components of the model. It probed into the factors influencing the perceived usefulness and e-learning behavioral intention of college students in private universities in Zhanjiang. The researchers put forward seven hypotheses to investigate the predictive roles of perceived ease of use, perceived usefulness, performance expectancy, effort expectancy, social influence, and attitude on e-learning behavioral intention, as well as the complex and subtle relationship between individual perceived ease of use and perceived usefulness. The survey participants were undergraduates from four secondary colleges of Zhanjiang University of Science and Technology. These secondary colleges have a large-scale operation and a certain number of the same public basic courses, so they were selected as research samples. All respondents possessed at least one semester's worth of e-learning experience and chose to participate in the questionnaire survey voluntarily. The research findings indicate that all the proposed seven hypotheses have received strong support and validation, which is conducive to achieving the research objectives.

The study yields several significant achievements. Perceived ease of use has a strong intervention effect on perceived usefulness, suggesting that when developing an e-learning platform, attention should be paid to facilitating students' operation and control. This is more conducive to helping students establish a belief in the perceived usefulness of the platform. Mailizar et al. (2021) indicated that the ease of use of the e-learning platform and the degree of energy saved perceived by undergraduates when using the system are beneficial for them to experience usefulness in completing their academic lives. Therefore, shaping the perceived ease of use of the system is of key significance for promoting individual perceived usefulness. The research further indicated that the perceived ease of use directly impacts students' behavioral intentions and exerts an indirect effect via perceived usefulness. Thus, perceived ease of use, as an individual belief of students, should become the key exploration object of educators, focusing on exerting its promotion effectiveness.

The target population on which this research centers is students in higher education institutions. Compared with other groups, students attach greater significance to the suggestions of teachers, parents, classmates, etc., which subtly impact their personal choices. These suggestions involve the application of new technologies, professional trends, personal development, and other fields and have important guiding significance for students. Olasina (2019) pointed out that valuable others are extremely important in shaping personal opinions. Social influence has had a positive effect on the influence of users' tendency to accept information technology. Therefore, higher education institutions should be aware of this situation and give sufficient attention and guidance in the education process.

Furthermore, both performance expectancy and effort expectancy exert positive predictive influences on behavioral intention. This aligns with the findings of previous researchers (Ain et al., 2016; Gunasinghe et al., 2020; Raman et al., 2014). The effect of effort expectancy is higher than that of performance expectancy in this research. This is because Chinese private undergraduates ' basic knowledge is relatively weak, and their enthusiasm for active learning is not high. Students are more concerned about the academic achievements brought about by the ease of using technology.

Attitude is a crucial influencing factor of behavioral intention, and this study also confirmed this point (Chang et al., 2015; Lee, 2010; Tsai et al., 2018). Students' optimistic attitude towards the e-learning system is conducive to students' higher electronic learning behavioral intention.

In conclusion, this study proposed a comprehensive conceptual model that can serve as a comprehensive foundation for studying learners' perceived usefulness and electronic learning behavioral intention. The results of this research on learners' intention to use e-learning are practically and theoretically reasonable.

5.2 Recommendation

This study investigated the factors influencing perceived ease of use, perceived usefulness, performance expectancy, effort expectancy, social influence, and attitude on the behavioral intention to employ e-learning among Zhanjiang University of Science and Technology undergraduates. Furthermore, it investigated the predictive influence of perceived ease of use on perceived usefulness. All six above factors positively correlate with behavioral intention and should be the main focus for college teachers and administrators. The intervention effect of perceived ease of use on perceived usefulness is the most pronounced among the factors considered. This indicates that during the design process of an e-learning system, a focus on ease of operation and manageability for students is paramount. Such an approach is more likely to foster students' belief in the system's usefulness, thereby enhancing the intervention effect on their behavioral intention towards e-learning.

Higher education institutions should recognize the intervention effect of the suggestions from parents, classmates, teachers, etc., on college students and offer full attention and guidance during the educational process. By providing comprehensive counseling services, it assists students in establishing sound beliefs regarding using the electronic system. Simultaneously, while training teachers, it is also essential to enhance the training of relevant knowledge and skills so that teachers can provide students with more outstanding and practical suggestions and guidance, enabling students to effectively utilize e-learning to support offline learning and better achieve personal goals.

Students in private undergraduate colleges typically have a relatively weak academic foundation. If they consider that using the system does not require excessive effort, they will likely be more willing to embrace the e-learning platform. Higher education practitioners should be dedicated to demonstrating to students the practical value of e-learning and the effectiveness of the operating procedures. It is practicable to elevate students' cognitive abilities and competencies by employing online training, in-person field guidance, and digital dissemination. This multifaceted approach serves to amplify both the behavioral inclination towards and the efficacy of utilizing e-learning platforms. Efficient teachers and administrators also need to handle communication with software development institutions deftly and actively provide feedback on various problems encountered by students during the system operation process, thereby improving the high-speed, effective, and flexible performance of the e-learning system.

To conclude, this furnishes management research and development directions for college educators, administrators, and even software system developers and contributes to promoting the better development of online and offline education.

5.3 Limitation and Further Study

Researchers carried out a meticulous exploration of this study. Nevertheless, certain limitations remain that demand particular attention. The subsequent suggestions are put forward for future research endeavors. Firstly, this study centered on undergraduates of private undergraduate higher education institutions as the analytical sample. Even though this design enables us to acquire an in-depth comprehension of this specific group, the research scope and the sample size are rather restricted, which might impact the universality of the research conclusion. Hence, future research should expand the sample coverage to enhance the representativeness of the research objects and establish a solid foundation for subsequent research. Secondly, the demographic targets of this study mainly concentrated on the student group, which, to a certain extent, constrained our understanding of the willingness to utilize e-learning platforms among other social groups (such as enterprise employees, civil servants, and researchers in research institutions etc.). Finally, this study predominantly adopted quantitative analysis methods. In subsequent research, qualitative analysis can assist with the research results. The research results can be comprehensively verified and profoundly discussed from multiple perspectives to reveal the internal mechanism of the intentions to use e-learning platforms more comprehensively.

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